



Original Article

Evaluation of Keyword Extraction using YAKE and KeyBERT in Text Preprocessing for Hoax News Detection Based on Bi-LSTM

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Abstract:

The spread of hoaxes through social media presents a significant challenge to the accuracy of public information. Automated detection based on natural language processing (NLP) offers a potential solution to this issue. This study investigates the impact of keyword extraction methods on the performance of hoax classification using the Bidirectional Long Short-Term Memory (Bi-LSTM) architecture. Two methods are evaluated: YAKE, which relies on statistical features, and KeyBERT, which utilizes semantic representations from the BERT transformer model. The IDNHoaxCorpus, an Indonesian-language dataset, serves as the experimental basis, undergoing preprocessing, keyword extraction, and model training stages. Evaluation metrics include accuracy, precision, recall, F1-score, and processing time. Results show that KeyBERT achieves higher accuracy and F1-score (82.56% and 73.30%, respectively) compared to YAKE (80.07% and 71.11%), but at the cost of significantly longer processing time (360 seconds vs. 13 seconds). These findings highlight a notable trade-off between accuracy and computational efficiency, which should be considered based on application requirements such as real-time systems or batch processing. This study underscores the importance of selecting appropriate feature extraction strategies in text-based hoax detection systems.

Keywords: Hoax, YAKE, KeyBERT, Bi-LSTM

Introduction

Digital technology and social media have revolutionized the way society views and accesses information. Social media platforms such as Facebook, Twitter, and Instagram enable news to spread rapidly and widely across different segments of the population ([Surianto et al., 2024](#)). Communication may affect the behaviour of its user, based on its performance as key element of communication, commonly known as channel or digital channel ([Agun et al., 2023](#)). This ease of access also opens up significant opportunities for the spread of hoaxes or false information, which can mislead the public and cause serious negative impacts, such as social unrest and horizontal conflicts ([Dwivedi et al., 2021](#)). The rapid virality of hoaxes on social media makes manual control ineffective, thus requiring an automated solution to detect such harmful content. Social media platforms possess the dual potential to generate both positive and negative societal impacts, influencing communication, information dissemination, and public perception. Based on [Azis \(2021\)](#), hoaxes can be classified as one of the negative consequences of social media, as they exploit the rapid spread of unverified content and contribute to misinformation.

The spread of hoaxes affects not only individuals but also has the potential to threaten political stability and national security. False information can trigger societal polarization and undermine public trust in official institutions. Automatic detection of hoax content is crucial to maintaining the integrity of public information and preventing massive misinformation from spreading in this digital era ([Caled & Silva, 2022](#)). Hoaxes have the potential to damage social structures, as they often contain information deliberately manipulated for specific purposes, such as propaganda or economic fraud. The existence of an automated detection system is vital as an early mitigation tool before false news spreads further to the wider public ([Xu & Kechadi, 2024](#)). Such systems help safeguard public information security while also enhancing digital literacy among society.

Various studies have shown that hoax detection efforts must be able to handle large volumes of data with the complex and dynamic characteristics of natural language on social media. Bidirectional Long Short-Term Memory (Bi-LSTM) is an advancement of conventional LSTM, with the ability to read input in both forward and backward directions, thus allowing the sentence context to be understood more comprehensively than unidirectional models ([Tagiphour & Ng, 2016](#)). Bi-LSTM achieved an accuracy of 96.48% in detecting hoaxes on social media, outperforming the unidirectional Recurrent Neural Network (RNN) model ([Aji & Setiawan, 2023](#)). The use of artificial intelligence in previous studies has proven to be an effective approach in detecting hoaxes, particularly through text processing using deep learning models such as Bi-LSTM. However, the success of such models highly depends on the quality of data preprocessing, especially in terms of keyword extraction that can accurately represent important information from the text. A model's performance in natural language processing is heavily influenced by the keyword extraction method used. The extraction process plays a vital role in transforming raw text data into feature representations that can be understood by the model. An appropriate extraction method enables the model to capture context, meaning, and relationships between words more effectively, thus improving prediction accuracy and performance.

Effective keyword extraction is essential in natural language processing because it allows models to capture both semantic and syntactic information that is



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crucial for improving prediction accuracy (Rico & Espada, 2025). YAKE (Yet Another Keyword Extractor) is known as a statistical-based keyword extraction method designed to work independently of large corpora and without requiring model training, making it suitable for applications with limited computing resources. KeyBERT, on the other hand, is an embedding-based keyword extraction method that leverages vector representations from the BERT model to generate more contextual and relevant keywords based on document content.

Literature Review

Sub 1 Hoaxes or Fake News

A hoax can be defined as the dissemination of news or claims that are not based on facts, often packaged in a way that appears convincing enough to influence public opinion. The main characteristics of hoax news include inaccurate information, emotional manipulation of readers, and rapid distribution through social media without verification of the truth ([Ajik et al., 2023](#)). The negative impact of hoax dissemination is widespread and dangerous to society. Hoaxes can create public confusion, exacerbate socio-political situations, and even threaten national security ([Yopita, 2024](#)). Public trust in mass media has also declined due to the proliferation of fake news ([Ali & Mirhoseini, 2023](#)). Hoaxes can influence election outcomes and create polarization among the public ([Teruel, 2023](#)).

Sub 2 Natural Language Processing (NLP)

Natural Language Processing (NLP) is a branch of computer science that focuses on the interaction between computers and natural human language in the form of text or speech ([Sulistyo, 2021](#)). The main functions of NLP in text processing include extracting important linguistic features such as word tokenization, stemming/lemmatization for base word normalization, and syntactic and semantic sentence analysis. According to ([Ornbay, 2024](#)), NLP enables computers to understand, analyze, and generate human language in a meaningful way. In the context of hoax detection, NLP is used to understand the structure and meaning of a text in order to differentiate between valid facts and misleading or false claims. This method allows the modeling of rare or unknown words by breaking them into smaller units, thus helping the model better understand the meaning of words in various forms and contexts ([Garí et al., 2021](#)).

Sub 3 Deep Learning in Text Classification

Deep learning is a subset of machine learning that uses multi-layered artificial neural networks to automatically learn complex data representations without the need for manual feature extraction ([Taye, 2023](#)). In natural language processing, particularly in text classification such as hoax news detection, deep learning offers significant advantages over traditional rule-based or simple statistical approaches ([Supriyono, 2024](#)). Research by [Zhang \(2020\)](#) shows that a combination of CNN and LSTM can improve hoax detection accuracy up to 90%. In fake news detection applications, several studies demonstrate that combinations of CNN-LSTM or Bi-LSTM with attention mechanisms result in higher accuracy compared to conventional single models ([Kumar, 2020](#)). Research by [Staudemeyer & Morris \(2019\)](#) also indicates that the use of hybrid models can enhance hoax detection performance by leveraging the strengths of each model.

Sub 4 Long Short-Term Memory (LSTM) and Bi-LSTM

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) specifically designed to overcome the limitations of standard RNNs, particularly the difficulty in learning long-term dependencies due to the vanishing gradient problem ([Staudemeyer & Morris, 2019](#)). The LSTM architecture consists of memory cells and three control gates—forget gate, input gate, and output gate—which allow selective retention, deletion, and reading of important historical information during the training process. Bidirectional LSTMs (Bi-LSTMs) are an extension of the LSTM architecture where the input is processed in two directions: forward (from the beginning to the end of the sequence) and backward (from the end to the beginning) ([Graves & Schmidhuber, 2005](#)). This enables the model to understand the full context before and after a specific token, thereby improving predictive ability, especially in complex natural language understanding tasks such as multi-class fake news classification ([Amalia et al., 2022](#)). Empirical research shows that the use of Bi-LSTMs provides a significant accuracy improvement compared to unidirectional LSTMs ([Saxena et al., 2019](#)). The strength of Bi-LSTMs in understanding bidirectional context is crucial in hoax detection, where the meaning of a sentence often depends on the words that come before and after. Research by Staudemeyer & [Morris \(2019\)](#) indicates that Bi-LSTM models can achieve up to 95% accuracy in detecting hoax news, making it one of the most effective methods in text classification.

Sub 5 KeyBERT

KeyBERT is a keyword extraction method that utilizes embedding representations from transformer-based language models, specifically BERT (Bidirectional Encoder Representations from Transformers). This method was developed to automatically generate relevant and contextual keywords from a text document. Technically, KeyBERT works by converting the entire document and candidate words/phrases into vector representations using BERT embeddings. Then, the words or phrases with the closest vector similarity to the overall document vector are selected as the main keywords. This approach enables keyword extraction based not only on word frequency but also on the context and semantic meaning within the text. The advantage of KeyBERT over traditional methods such as TF-IDF or RAKE lies in its ability to capture word context, resulting in keywords that are more relevant and informative, especially for documents written in complex natural language.

Sub 6 YAKE

YAKE (Yet Another Keyword Extractor) is an automatic keyword extraction method based on statistical features and is designed to work independently without requiring large corpora or prior model training. YAKE relies on simple statistical features computed directly from the text, such as word frequency, word position within the text, and the local context of the word, to determine the relevance of each word or phrase as a keyword. The main advantage of YAKE is its ability to extract keywords with high computational efficiency and without relying on external training data, making it well-suited for applications with limited computing resources or those requiring fast and lightweight extraction processes. Additionally, YAKE can be applied to various languages and document types without the need for complex adjustments. YAKE calculates a relevance score for each candidate keyword based on a combination of several factors, including word distribution in the document and the

degree of variation in word usage. This approach enables YAKE to automatically and effectively identify the most representative and important keywords in a text. The YAKE method is widely used in information systems and natural language processing (NLP), especially when speed and efficiency are priorities—such as in keyword extraction systems for document analysis, information retrieval, and content indexing.

Research Method

Research Design

This study adopts a quantitative research approach to evaluate the effectiveness of two keyword extraction methods YAKE (Yet Another Keyword Extractor) and KeyBERT in the text preprocessing stage prior to feeding the data into a hoax detection model based on Bidirectional Long Short-Term Memory (Bi-LSTM). The main objective of this design is to analyze how the quality of keyword extraction influences the hoax prediction accuracy on Indonesian-language texts.

Research Flow Diagram

To illustrate the workflow of this research, a flowchart is used to visualize the key stages undertaken. This diagram presents the sequential process from the initial data collection to the evaluation phase of the Bi-LSTM based hoax detection model. The steps in the diagram reflect the systematic approach applied in the study, starting with data crawling or data acquisition, followed by a series of text preprocessing steps, such as text cleaning, stopwords removal, and tokenization. This stage also includes the keyword extraction process, which is the main focus of the research, by comparing two methods: YAKE and KeyBERT.

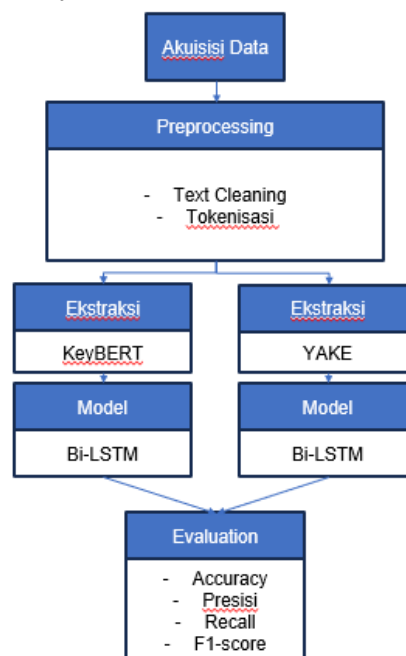


Figure 1. Research Flow Diagram

The research was conducted through several systematic stages aimed at evaluating the performance of the keyword extraction methods YAKE and KeyBERT

in supporting hoax news detection based on Bidirectional Long Short-Term Memory (Bi-LSTM). The research process begins with data collection and ends with model performance evaluation. The research flow diagram, which serves as a technical guide during the research and model implementation process, is shown in Figure 3.1. The diagram systematically describes the stages of the research, starting from data acquisition (data crawling) to the evaluation of the Bi-LSTM model's performance. Each component in this workflow is designed to be integrated with one another, forming a complete and reproducible working process.

The first stage is the data acquisition process. The dataset used in this study is sourced from a GitHub repository named IDNHoaxCorpus, which is publicly available at <https://github.com/9uz/IDNHoaxCorpus>. This dataset contains a collection of hoax and non-hoax news articles in the Indonesian language that have been labeled and compiled specifically for research purposes in the field of hoax detection. The data selection is focused on keywords often associated with hoax content, such as health issues, political discourse, and other viral news topics. Once the data has been collected, the preprocessing stage is carried out to clean and prepare the data before it is processed by the machine learning model. This stage includes text cleaning, which involves removing irrelevant characters such as punctuation, URLs, mentions, and hashtags that may interfere with the training process. Then, stopword removal is performed using NLP libraries such as Sastrawi or NLTK to eliminate common words that do not contribute significant meaning to the context. The next process is tokenization, which splits sentences into tokens or word units. This is done using the AutoTokenizer from NLTK to ensure that the tokenization results are compatible with the model used.

The next phase is keyword extraction, which is the main focus of this research. Two methods are evaluated: YAKE (Yet Another Keyword Extractor) and KeyBERT. YAKE is an unsupervised method that relies on local statistical features such as word frequency, position, and contextual distribution to assess the importance of a word or phrase. In contrast, KeyBERT uses embedding from the BERT language model to represent the semantic meaning of the text and then calculates the cosine similarity between the document and candidate words or phrases to determine the most relevant keywords. These two methods are applied during the preprocessing phase, and their results are compared based on their impact on the performance of the hoax classification model.

The next stage is modeling. The main model used is the Bidirectional Long Short-Term Memory (Bi-LSTM), with input in the form of vector representations resulting from keyword extraction. The encoding process is applied to two types of inputs, namely the entire tweet text and the extracted keywords. The encoding results are then passed through a Global Average Pooling layer to reduce dimensionality and generate concise representations. The representations from the tweets and keywords are then combined in the Concatenation Layer, followed by several Dropout Layers to prevent overfitting. Finally, the output is passed to a Softmax Output Layer for the final classification into two classes: hoax and non-hoax. The final stage is model evaluation. The evaluation is conducted using accuracy as the primary metric. In addition, supporting metrics such as precision, recall, and F1-score are also used to provide a comprehensive overview of the model's performance. The research is carried out under two different scenarios: first, the

model is executed using keywords extracted by YAKE, and second, the model is executed using keywords extracted by KeyBERT. The results of both approaches are then compared to draw conclusions regarding which keyword extraction method is more effective in supporting hoax news detection. The performance evaluation is conducted using a set of classification metrics including:

1. **Accuracy** measures the proportion of correct predictions out of all test data, indicating how well the model is able to correctly classify both hoax and valid news. It is calculated using the formula:

$$Accuracy = (TP + TN) / (TP + FP + FN + TN) \quad (1)$$

2. **Precision** evaluates the model's accuracy in classifying a news article as *hoax*. A high precision value indicates that most of the news articles predicted as *hoax* are actually *hoax*. The formula for precision is

$$Precision = TP / (TP + FP) \quad (2)$$

3. **Recall**, on the other hand, measures the model's sensitivity—its ability to identify all actual *hoax* cases. A high recall means the model successfully captures most of the *hoax* news in the dataset. It is calculated as:

$$Recall = TP / (TP + FN) \quad (3)$$

4. **F1-score** is the harmonic mean of precision and recall. This metric provides a balance between precision and recall, especially when dealing with class imbalance. The formula for the F1-score is:

$$F1.score = 2x (Recall \times Precision) / (Recall + Precision) \quad (4)$$

Results & Discussion

Data Analysis Results

The data analysis process in this study began with an exploration of the data distribution based on the available labels. In the initial stage, data labeled with a "?" indicating the absence of a clear class annotation or considered as noise were identified. After removing the data with the "?" label, further analysis was conducted on the remaining data to understand the distribution of the most frequently occurring topics in the tweets.

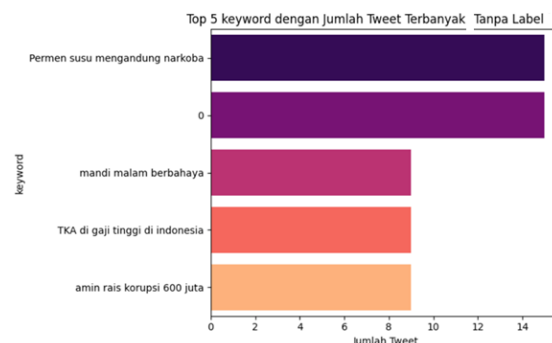


Figure 2. Op 5 Keywords Based on the Highest Number of Tweets.

Figure 2. presents the top five keywords with the highest number of tweets in the dataset after noise-labeled entries were removed. The keywords "Candy contains narcotics" and an empty entry ("0") appear as the two most dominant topics, each occurring in approximately 15 tweets. These are followed by three other keywords: "mandi malam berbahaya", "TKA di gaji tinggi di indonesia" and "amin rais korupsi

600 juta" each appearing 9 times. From these findings, it can be concluded that the most frequently discussed issues in the dataset tend to revolve around sensitive and controversial topics such as health, politics, and labor. The presence of an empty entry as one of the top keywords also becomes a significant note, as it indicates a possible lack of structure in the data or insufficient preprocessing. This highlights the importance of effective keyword extraction in text data analysis, particularly in hoax detection tasks. Proper keyword extraction allows the model to obtain more informative and contextually relevant feature representations, which significantly contributes to the final performance of the classification model—both in improving detection accuracy and reducing misclassification errors.

Table 1. Comparison of Keyword Extraction Methods Results

Learning Algorithm	Extraction Meethod	Classification Result	Count
Bi-LSTM	YAKE	TN	312
		TP	138
		FP	50
		FN	62
	KeyBERT	TN	305
		TP	142
		FP	52
		FN	63

Based on the evaluation results, when using the YAKE method, the model correctly classified 312 instances as non-hoax (True Negative – TN), and correctly identified 138 instances as hoax (True Positive – TP). However, it misclassified 50 non-hoax instances as hoax (False Positive – FP), and failed to detect 62 hoax instances (False Negative –FN). In contrast, using the KeyBERT method, the model achieved 311 TN, 145 TP, 49 FP, and 56 FN. To assess the overall performance of both keyword extraction methods in the context of hoax classification using the Bi-LSTM model, several key evaluation metrics were applied, including accuracy, recall, precision, and F1-score. These metrics provide a comprehensive view of the model's ability to classify hoax and non-hoax data accurately and to effectively detect positive (hoax) instances.

Table 2. Comparison of Bi-LSTM Model Performance

Learning Algorithm	Extraction Meethod	Metrics Performance Model			
		Akurasi	Recall	Presisi	F1-Score
Bi-LSTM	YAKE	80.07%	69%	73.40%	71.11%
	KeyBERT	82.56%	72.14%	74.74%	73.30%

Based on Table 4.2, it can be observed that the performance of the Bi-LSTM model shows a significant difference when combined with two different keyword extraction methods, namely YAKE and KeyBERT. The model using KeyBERT as the keyword extraction method achieved an accuracy of 82.56%, which is higher than YAKE's 80.07%. In addition, the recall score of KeyBERT was also superior, at 72.14%, compared to 69% for YAKE. This indicates that KeyBERT is better at identifying or capturing relevant data, thus reducing the number of missed instances (false negatives). In terms of precision, KeyBERT recorded 74.74%, slightly higher

than YAKE's 73.40%, meaning that the predictions generated by the model were more accurate. Overall, the F1-Score of the model with KeyBERT was also better, at 73.30%, compared to 71.11% for YAKE. These results suggest that using KeyBERT in the keyword extraction process contributes more positively to the performance of the Bi-LSTM model, especially in maintaining a balance between precision and recall.

From this evaluation, it is clear how each keyword extraction method contributes to the model's performance in different ways. The YAKE method excels at minimizing false positive classifications, making it more accurate in identifying non-hoax news, while still maintaining a balance between precision and recall. Conversely, the KeyBERT method performs better in detecting hoax news, with a higher true positive value, and provides improvements in both accuracy and recall. These differences illustrate a trade-off between precision and recall, which is an important consideration when selecting a keyword extraction method, depending on the application's priority—whether to minimize false hoax detections or to improve overall hoax identification.

In addition to evaluating classification performance based on metrics such as accuracy, precision, recall, and F1-score, processing efficiency is also an important aspect to consider, especially in the development of real-time systems or systems that must handle large volumes of data. Slow processing can hinder the overall system performance and may not be suitable for deployment in environments with limited resources or the need for rapid response.

Table 3. Processing Time Comparison of YAKE and KeyBERT

Extraction Methods	Rata-rata Waktu Proses (Second)
YAKE	13
KeyBERT	360

The time measurement in Table 4.3 represents the processing time for the keyword extraction methods YAKE and KeyBERT using the same dataset. The testing results show a significant difference in processing time between the two methods. YAKE was able to complete the keyword extraction process in an average of 13 seconds. YAKE uses a statistical-based approach to assess the importance of words in a document without relying on machine learning or complex semantic representations. This makes YAKE highly efficient and fast in terms of computation. On the other hand, the KeyBERT method took approximately 6 minutes to complete the extraction process on the same dataset. This difference indicates that while KeyBERT provides more contextual extraction results and positively impacts classification performance (especially recall and accuracy), the trade-off in processing efficiency becomes a critical consideration.

YAKE, meanwhile, demonstrates high time efficiency while still producing competitive model performance. Therefore, selecting a keyword extraction method should consider the trade-off between result effectiveness and processing efficiency, depending on the specific needs of the system to be developed. If the system demands fast responses and high scalability, YAKE would be a more suitable choice. However, if the main objective is deeper extraction quality and improved hoax detection, KeyBERT remains a viable option despite its longer processing time.

Conclusion

Based on the results of the research conducted on the application of YAKE and KeyBERT feature extraction methods in hoax news classification using the Bi-LSTM algorithm, several important conclusions can be drawn. First, the need for feature extraction arises from the presence of empty ("o") or meaningless features that may interfere with the model's performance if not properly addressed. Therefore, a keyword extraction process is essential to obtain more relevant and meaningful feature representations, both statistically and semantically. Second, the comparison between YAKE and KeyBERT shows that both feature extraction methods have their respective advantages. YAKE excels in terms of computational efficiency and reducing the False Positive rate, while KeyBERT is able to deliver better overall classification results, particularly in improving accuracy, recall, and F1-score. KeyBERT demonstrates stronger performance in accurately detecting hoax news (True Positive), although it requires more time for extraction. Lastly, there is a significant trade-off between efficiency and accuracy. YAKE is suitable for applications that require high-speed processing, such as real-time systems, while KeyBERT is more appropriate for systems that demand high detection accuracy, such as batch evaluation systems or analytical reports that are not time-sensitive.

Suggestion

Based on the findings, it is recommended that future research prioritize the integration of semantically rich feature extraction techniques to enhance the performance of hoax news classification models. Academically, exploring hybrid or ensemble approaches that combine the strengths of YAKE's efficiency with KeyBERT's semantic depth may yield improved results. Additionally, the development of adaptive feature extraction frameworks that dynamically balance speed and accuracy could be a promising direction. From a practical standpoint, YAKE is recommended for real-time or resource-constrained systems where rapid processing is critical, while KeyBERT is more suitable for high-accuracy applications, such as post-event analysis or batch evaluations. Practitioners should align the choice of extraction method with specific operational goals, balancing the trade-offs between computational cost and classification performance.

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